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Logics in Animal Cognition: Are They Important to Brain Computer Interfaces (BCI) And Aerospace Missions?

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Abstract—Conventional wisdom is that logic and language are tightly connected to logics in human cognition. However, recent studies have revealed that, in animal cognition, there exist logics that do not depend on languages. In other words, logical behavior is not human brain specific. At least four logics: *perceptual logic*, *technical logic*, *social logic*, and *inference logic* have been studied in animal cognition. Despite the obvious differences between animals and humans in using languages, recent studies confirm that both humans and animals utilize the so-called *sensor brain maps* for most sensory modalities: populations of neurons are selectively tuned to different stimulus features or feature combinations (Ewert 2005, Ma and Krings 2009). This commonality suggests that the studies of animal logics should also be insightful for understanding human logics. After briefly reviewing some of the recent advances in animal logics research, we turn to a more practical research field—the Brain Computer Interface (BCI) [also known as Brain Machine Interface (BMI)] in biomedicine. BCI promises to provide non-muscular communication and control for people with severe motor disabilities. A fundamental goal of BCI is to translate thought or intent into action with brain activity only (Birbaumer 2006). If we recognize that logic is about the way of thinking and it is probably the most reliable and possibly most efficient way to understand thoughts, an interesting question could be: will the understanding of animal logics be very helpful for BCI research? The current BCI research is primarily targeted for rehabilitation applications. In this article, we also discuss the potential of using BCI techniques in aerospace systems and space explorations. One can imagine the potential that an astronaut operates a robot device by only thinking. Perhaps a revolutionary breakthrough from BCI technology can be the '*copiloting*' of aerial vehicles by multiple pilots including some who stations at the ground. This copiloting not only reduces the stress (brain fatigue) of pilots, but also enhances the reliability and fault tolerance of aerial vehicles. [1 2]

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1. Introduction

Brain Computer Interface (BCI) or Brain Machine Interface (BMI) is aspired by the goal to activate electronic or mechanic devices with brain activity only. The active research of the field only stated in late 1990s, but stunning advances have been made in its first decade (Lebedev and Nicolelis 2006). The envisioned applications of BCI are of extreme significance in biomedicine, with the promising to allow direct brain communication in completely paralyzed patients and restoration of movement in paralyzed limbs (Birbaumer 2006). BCI is fundamentally different from other assistive technologies in biomedicine in the way that it essentially provides a new brain output pathway. Intent, which is normally communicated by speech or by behavior (another motor action), is encoded from brain signals in BCI so that a computer can translate it into control of a device such as a computer cursor or a neuroprosthesis (Wolpaw 2007).

There are two types of BCI: invasive BCIs that use activity recorded by brain implanted micro- or macroelectrodes, and noninvasive BCIs that use brain signals recorded with sensors outside the body boundaries. According to Wolpaw's (2007) survey, in the last decade, Brain computer interface (BCI) or brain-machine interface (BMI) has turned from a field with six to eight research groups into a burgeoning enterprise with more than 100 groups worldwide. BCI has the potential to provide valuable new option for restoring communication and control to people with severe disabilities, but it also faces enormous difficulty and furthermore the origin of the difficult is not clear (Wolpaw 2007).

The problem BCI tries to address is essentially to read intention or translate thought into action with brain activity only (Birbaumer 2006, Wolpaw 2007). As indicated by Birbaumer (2006), this essence is another formulation of the brain-behavior relationships in cognitive neuroscience and psychophysiology. BCI research indeed stimulates the long-held aspiration to detect and translate emotion and though from brain signals (Birbaumer 2006). The idea of 'reading thoughts' has documented as early as 1920s by Berger et al.

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[2] IEEEAC paper #1638, Ver. 7.

(1929) who explored the possibility of processing EEG waveforms utilizing powerful mathematical analyses (Birbaumer and Cohen 2007). Therefore, it is clear that the relationship between BCI and cognition science has been clearly established from the start of BCI.

Of course, animals (mainly primates) have been the subject of BCI research, particularly with the use of invasive BCI techniques (Carmena et al. 2003, Lebedev and Nicolelis 2006). Nevertheless, the perspective of this article is very different from existing studies, in which animal brains were used as 'substitutes' for human brains to test BCI techniques. In contrast, we are concerned with the potential of analyzing animal logics, which might be simpler than human logics, for inspiring BCI research.

In the following, we first briefly review some of the recent advances in the field of animal logics in Section 2. If there are commonalties between the underlying neural signals for animal logics and human logics, then the study of animal logics may offer important insights for BCI research. In Section 3, we make some conjectures on the potential inspirations that animal logics research may produce for BCI field. Section 4 discusses the potential of BCI applications in future space missions. In Section 4, we propose some promising BCI research projects that should benefit aerospace engineering and space exploration missions. One example of the perspective proposals is the application of BCI technology to address the massive pilot workload challenges in fighter aircrafts as well as the similarly important issue in unmanned air vehicle (UAV) ground control stations. At least, the measurement techniques developed in BCI research can be applied to analyze the brain fatigue of pilots. Yet, we believe that a potentially revolutionary technology from BCI research can be the 'co-piloting' of aerial vehicles by multiple pilots simultaneously. Some of the 'copilots' can even be stationed on the ground. There should be at least two significant benefits from the copiloting technology. First, it should help to relieve the fatigue of pilots. Second, it should enhance reliability and fault tolerance of the aerial vehicles.

It should be noted that BCI is different from Human Computer Interaction (HCI) [also known as CHI (Computer-Human Interaction), or MMI (Man-Machine Interaction)], which sets a long-term goal to design systems that minimize the barrier between the human's cognitive model for their intentions and the computer's understanding of the user's task. Since animal logics does not depend on languages and is therefore much simpler than human logics, but still functionally adequate in its own right. It is our opinion that the contents discussed in this article should also be helpful for achieving the long-term goal set for HCI. We also argue that, in aerospace systems and space exploration missions, the integration of BCI and HCI, further augmented with the potential inspiration from animal logics research, may generate additional synergetic advances for the future engineering technology.

2. Some Recent Advances in Research on Animal Logics

Dukas (1998) defined animal cognition as "neuronal process concerned with the acquisition and manipulation of information by animals." As reviewed by Ewert (2005), both animals and humans relate their perceptual worlds with their sensory systems and basic functions involving stimulus recognition and localization. In both animals and humans, populations of neurons are selectively tuned to different stimulus features or feature combinations. This is the so-called *sensory brain maps* and is true for most sensory modalities. The commonalities between animals and humans challenge the notion of lower and higher organisms. An important feature of neuron networks is that they are multipotent, or with various degrees of plasticity. Specifically, the characteristics of stimulus inputs and "openness" of the brain region receiving the inputs dynamically determine perceptions (Ewert 2005). This feature has inspired the artificial neuron network (ANN) theory. In a "recursive" application, Enquist and Ghirlanda (2005) systematically applied ANN to model animal behavior.

The term Logic has dual meanings: a way of thinking or the science of reasoning (Watanabe and Huber 2006). The former meaning is what we use in this article, and often the meaning in the study of animal cognition. The scientific study of animal logics begins much later than the studies of humans' logics, and the approaches and terminology are often deeply rooted in the study of human beings. The so-called "animal model anthropocentric view" refers to using animals as modeling systems for understanding humans (Watanabe and Huber 2006). Therefore, two extremes should be avoided in study animal logics: denying the existence of animal logics or totally generalize the approaches and results from study of human logics and minds. The former was characterized by the argument that animals do not use languages and therefore they cannot be rational or possess minds, which is an outdated view. The latter is not scientific either because human brain is indeed the most complex cognition machine and animal languages discovered to date obviously have no way to match the complexity and versatility of human languages. Then a natural question is: what is the significance of studying animal logics? Particularly, given the simple mind or low intelligence of animals compared with human beings, does the study of animal logics and minds have any significance for computer scientists? In other words, why do not we just study and learn from human cognition?

The answer to the above questions should be a solid yes. We just emphasize three arguments here: the criteria we judge the "success", "advanced", "higher" in classifying animals are anthropocentric. Even if objective criteria such as phylogenetic distances are used, the answer still depends on particular perspective. For example, from the functional perspective, it may be inappropriate to conclude that bird flight is advanced than insect flight, although birds are much more "advanced" than insects from the perspective of evolution history. Dumb-agent-like swarm intelligence in social ants probably is perfectly adequate for ants' society. It is estimated that the social termites and ants (with about 13,000 species) alone account for approximately 30% of the entire animal biomass (Wilson 1990). Nevertheless, social insects make up only about 2% of the identified insects species. Therefore, being simple-minded is not necessarily a bad thing in nature (Ma and Krings 2009, Ma 2010). The second argument we wish to emphasize is that since language is often not used in animal logics, the decision-making without language may be easier and more practical to emulate with computers.

The third argument is reviewed by Watanabe and Huber (2006). Many philosophers and psychologists believe that human brain follows logical rules. However, it is now also well accepted that human rationality is limited and perfect rationality only widely exists in some restricted areas (e.g., scientific reasoning). One explanation for this phenomenon is that perfect rationality may be too computational expensive because perfect rationality is likely to require solutions for hard optimization problems. Therefore, heuristic approaches that are effective in obtaining satisfactory solutions are used by brains to achieve rationality.

The relationship between logic and language has been studied extensively in human cognition, but the conclusion is far from certain as supporting experimental data exist for even opposing hypotheses. Some researchers claim that language is required for human logics and they believe that humans have a mental or natural logic. This mental logic is in the form of a set of simple inference rules, which are necessary for understanding language and logic reasoning. Furthermore, these rules are universal and can be expressed by any human languages (e.g., Braine and O'Brien 1998, Watanabe and Huber 2006). The opposing hypothesis is that the so-called "logico-linguistic rules" are not required for reasoning, and, instead, a "visio-spatial workspace" is necessary for cognition to happen (Johnson-Laird 2001, Watanabe and Huber 2006).

It is now clear that logic behavior is not humans specific, but differences indeed exist between human and animal worlds (Watanabe and Huber 2006). For example, animals are particularly poor in learning symmetry ($A=B \Rightarrow B=A$) and transitivity ($A=B$ and $B=C \Rightarrow A=C$), although they are capable to learn sameness ($A=B \Rightarrow B=A$). This lack of learning two features in an equivalence relation is due to the fact that corticocortical fiber connection is poorly developed in animal telencephalon, which seems only well-developed in human brains. This also makes that areas in animal brain can be relatively more independent than in human brains.

Watanabe and Huber (2006) emphasized that basic requirement for logical reasoning is the abstraction process, "which is the identification of regularities in the environment and the formation of inner models or representations." This abstraction is also necessary for logical and mathematical reasoning. However, for logical reasoning, it is based on coordinated (communicative) actions. As stressed by Watanabe and Huber (2006), language can also coordinate actions, the root of logical reasoning has not been found in languages. What is important is that there are simple abstraction and complex abstraction, the latter are from the objects in the environment through experience and can generate physical knowledge. The transitions between the two types of abstractions are gradual, which might explain the obvious continuity between animals and human logics (Watanabe and Huber 2006)

Complex human cognitions such as reading and math skills are considered dependent on a set of building-block systems developed in early human ontogeny and phylogeny (Spelke 2000). This is called "core knowledge." The power of human intelligence is amplified by the extraordinary flexibility achieved by combinatorial integration of the core knowledge, with natural language and as the richest combinatorial system and pure mathematics as the most striking intellectual product (Watanabe and Huber 2006). An alternative explanation for the exceedingly remarkable feat of human cognition is the hypothesis that cultural evolution has played significant role in the development of human intelligence.

At least four categories of logic have been studied in animal cognition: perceptual logic, technical logic, social logic, and inference logic. The following is a brief summary of these studies.

Perceptual logic—This logic is related to the simple abstractions in the sense defined by Piaget (1970). Perceptual logic is a generalization that categorizes natural classes based on perceptual similarity (Marsh and MacDonald 2008). Lea et al (2006) reviewed the animal logics in processing of stimuli. The argument was that any discussion of animal logics should start with perceptual logic or the logics involved in perceiving and representing stimuli from environment. One example of perceptual logics in animals is that some animals can reconstruct 3-D world from the 2-D retinal image. One important point Lea et al. (2006) emphasized is that perceptual analysis (logic) might be perfected before the cognitive analysis in the evolutionary history of vertebrates; however; alternatively different taxa may relieve themselves from the perceptual logic and adopt more a abstract logic to different extents. Therefore, animals may be intelligent with vary different ways.

Benard et al. (2006) reviewed similar trend in insects with honeybee as a model system. They concluded that honeybees exhibit the so-called positive transfer of learning (Robertson 2001). This means that honeybees can compare stimuli and categorize stimuli into different generalizations, which allows them to respond appropriately towards novel stimuli (Giurfa 2003). Positive transfer of learning is much more advanced and sophisticated than the elemental associative learning because it allows animals to respond to novel stimuli or can generate adaptive response in new context. The evidence therefore clearly put honeybee cognition in par with vertebrates such as pigeons or even primates. Yet, until recently, the term cognition is often avoided in invertebrate research.

The human brain has the ability to perceive partially occluded objects as whole objects because brain represents visual objects as continuous bounded units in space and time (Spelke 2000, Sovrano and Bisazza 2008). This ability is called "amodal" completion and has been discovered in mammals, birds, and the first experiment evidence in fish is reported by Sovrano and Bisazza (2008).

Technical Logic—This type of logic is concerned with tool using and tool making, both of which involve complex cognition mechanisms and the latter demands more sophisticated cognitive ability and motor skills (Hunt et al. 2006, Huber and Gajdon 2006). Recent studies confirmed that the Technical intelligence hypothesis originally proposed by Byrne (1997) in the study of primates also apply to some birds. Hansell's (2005) presented a comprehensive introduction on animal architecture, dominantly in home-building. Bees, termites and ants again are in the elite groups in terms of home (nest) making capacities.

Social Logic—Social manipulation (deceit) and imitation are example behaviors that social logic is in control. Bugnyar and Heinrich (2006) described tactical deception ravens may adopt when storing or pilfering food. Zentall (2006) presented a theoretical analysis of imitation, which discerns opaque imitation from other forms of social learning, and maintained that true imitation involves some degree of intentionality and goal directedness, i.e., cognition and logic are involved. Topal et al. (2006) discussed an advanced form of imitation (generalized imitation), which demonstrates that a dog can imitate by simply observing an spontaneous action sequence, in terms of the initial state, the means and the goal (Watanabe and Huber 2006).

Inferential logic—This seems to be the most sophisticated form of logic without using language. An example of the inferential logic is the number counting and summation. It was generally accepted than non-human animals generally can understand less than four numbers due to lack of languages. Dacke & Srinivasan's (2008) experiment with honeybees confirmed that bees can count up to four objects and that bees largely count sequentially.

Agrillo et al. (2008) studied quantity discrimination of fish prompted by the behavior that some fish spontaneously join in the largest shoal, which suggests that fish can make numerical judgments even large numerosities (>4) are involved. Agrillo et al (2008) found that mosquito fish use two distinct systems for quantity discrimination. One is the traditionally hypothesized for infants and primates, counting up to 4 objects. In the mean times, mosquito fishes indeed can discriminate size of groups spontaneously. They hypothesized that mosquito fishes do not use numerical representation; instead, they base their choice on non-numerical variables that are correlated with shoal size.

Pepperberg (2006) reviewed the numerical competence of Grey parrot and claimed that this parrot (named 'Alex') can quantify and comprehend six items using vocal English labels. It was also found that he has a concept of zero and can sum up small numbers. The inferential logic shows that animals such as parrot and primates may understand number symbols as abstract representations of real-world collections. Aust et al. (2008) compared the inferential logics among pigeons, dogs and humans, and they found that none of the pigeon, half of the dogs and almost all humans passed the inferential logic tests.

An important point that is particularly worthy of emphasizing is that despite the existence of the above four categories of logic , which apparently are not dependent on languages, animals do not lose their capability in using associative process or even rules of thumb to solve problems (Watanabe and Huber 2006). These logics are more sophisticated abstractions. However, why they are not dominant in animal cognition is still an enigma.

3. IS THE UNDERSTANDING OF ANIMAL LOGICS VERY HELPFUL FOR BCI RESEARCH?

To answer the question raised in the title of this article, we believe that the excellent review by Wolpaw (2007) on the challenges BCI face provides some hints at the answer. In the following, we first briefly summarize Wolpaw's conclusion.

As reviewed by Wolpaw (2007), a fundamental difference between BCI and normal motor actions is that normal motor actions are produced by spinal motoneurons; whereas, BCI outputs are produced by brain signals in one or more areas of the brain that reflects the intention to be captured. In normal life, brain signals are the participants of the motoneuron control, and in BCI, they become the excusive output of CNS (Central Nerve System), or the final product. In other words, the brain neurons that produce brain signals now need to assume roles which are normally performed by spinal motoneurons. According to Wolpaw (2007), the brain neurons' adaptation to this new role is possible but imperfect. This biological reality set a limitation for the BCI functionality.

There are two contrasting approaches for BCI development: the process-control approach and the goal-selection approach. In the former approach, the BCI tries to process all the complex high speed interactions necessary for smooth and accurate movement; essentially, BCI directly controls muscles or a cursor or a device such as robotic arm. In the latter approach, BCI focuses on 'detecting' the intention and sets the desired actions, where the muscle (or device) control is handled by sophisticated software. Given the biological limitation discussed above, Wolpaw (2007) suggested that the goal-selection approach should be the winning strategy in order to develop more reliable and accurate BCI.

As reviewed in Section 2, both animals and humans possess sensor brain maps—populations of neurons are selectively tuned to different stimulus features or feature combinations. Mechanisms for brain-produced-response may be viewed as animal logics property sets whose *sensor brain map*s define a functional description of stimuli-to-response behavior. A classification based on lower- to high-order animal logics may provide the BCI with response strategies that comprise a graduated set of primitives that can be manipulated quickly (i.e., computational fast) and (depending upon the circumstances) highly reliable. The BCI implementation could then be organized as a tool set of animal logics libraries where set operations determine the appropriate responses.

Moreover, the animal logics mechanisms for brain-produced-response to stimuli may help in better enhancing and preparing the human capacity to react to situations that are common place and instinctive to animals with much less neurological development. Examples of peripheral sensing are prevalent in the animal logics literature, and the understanding of these mechanisms may have a significant impact to mission critical BCI responses. In addition, we note that animals with more primitive neurological organization have developed a greater advantage for survival than those with more advanced neurological systems. We point to the multitude of insect that have and still dominates the earth, as an example. The integration of these primitive logic strategies may even motivate the development and use of *primitive* sensing devices that may add an additional degree of freedom to the determination of critical-information and appropriate-response. Integrating these senses into the BCI could also enhance situation awareness and accelerate human-response training.

Therefore, the mechanisms for brain-produced response to stimuli are similar in both humans and animals. It is hoped that the study of animal logics may help to better understand human logics. Especially, animal logics usually do not depend on languages, which makes the study much simpler.

A key technical aspect of BCI research is to improve the brain signal processing techniques and selection of features that are translated into control commands. There are three categories of feature selection techniques: filters, wrappers and embedded methods. These are essentially classification algorithms. A problem with these classifier algorithms is that they cannot explain the process by which a classification is made (Lakany and Conway 2007). Lakany and Conway (2007) tried to add the explanation ability to the classifier by analyzing pre-movement signals based on notion that a progressive rise in motor area activity often precedes the voluntary movements or the so-called readiness potential. While this readiness potential may be helpful to add the explanation power of the classifier algorithm, it does not change the algorithms used (they still used the SVM, Support Vector Machines). We concur with Lakany and Conway (2007) that the explanation power is important; however, we suggest that a more effective approach to augment the explanation power of BCI may be through analyzing the logics of the decision-making because new algorithms for BCI interface may be developed based on the analysis.

4. THE APPLICATION POTENTIAL OF BCI TECHNIQUES IN AEROSPACE MISSIONS

4.1. Existing Research

Menon et al. (2009) suggested the use of non-invasive BCI for space system controls. They are optimistic that the application of BCI techniques in space system control, although not yet feasible, should happen in the near future. The main anticipated advantages of BCI techniques in space exploration include: the possibility of reducing the need for EVA (Extra-Vehicular Activity), reducing control input delays, allowing multitasking, enhancing interfaces with artificial intelligent systems during the intra-vehicular activities, and augmenting the operation capabilities of astronauts (Menon et al. 2009). For example, multi-teleoperations may be launched simultaneously from a single BCI system, or alternatively, a team of astronauts may command a device during intra- or extra-vehicular operations.

Menon et al. (2009) argued that, to be useful for space explorations, the following properties are necessary: non-invasiveness, high reliability, high efficiency, high sensitivity, sufficient comfort, electromagnetic compatibility (non-interference), and robustness.

To apply BCI techniques to space system control, some special issues such as: human physiology in space, microgravity, and effects of radiation must be thoroughly studied within the context of BCI techniques because these issues may have profound influences on brain activities (Menon et al. 2009). In addition, there are other significant challenges that include low throughput, high error rate, autonomy, cognitive load for the development of BCI techniques. These challenges exist for both rehabilitation and space mission applications, but more demanding in the latter application. It is hoped that the study of animal logics will offer some inspiration to address these challenges.

4.2. Aviation Applications

As in space applications, in both military aviation, and commercial aviation, applying BCI to both vehicle and mission system control requires a very high standard of reliability and determinacy, plus the other desirable features

Menon et al (2009) identify. Other less critical applications may be available for BCI but these are of lesser interest.

In military aviation, and to a lesser extent in commercial aviation, pilot workload can be very high in some flight segments, interspersed with other segments with low workload due to automated flight management provisions. The transitions between these may be unpredictable and uncontrollable, possibly resulting in poor situational awareness if pilot attention flags during low workload segments.

High pilot workload and distraction is often related to multiple & diverse concurrent tasking because automation of aircraft and mission systems enables the addition of functions earlier handed by other crew members to pilot tasking. One side effect of this trend is the combining of multiple observation and control tasks into common human/computer interface (HCI) (both displays and control features (stick, pedals, buttons, switches, etc.), often by introducing mode specific display & control functionality that results in potentially confusing complexity requiring heightened pilot attention & cognition. The HCI implementation of such complexity may lack the intuitiveness desirable in such circumstances, particularly when such functionality is added incrementally during development or in service.

In the military arena there is growing interest in unmanned air vehicles (UAV), some piloted from ground stations but in future more likely operating primarily under autopilot control even during takeoff, approach and landing. Again, this development is likely to lead to multitasking, e.g., payload (sensors & weapons) operation or flight management of multiple vehicles. The combination of piloting a manned vehicle while managing one or more UAV is a likely development.

Both BCI and conventional HCI integrating knowledge of "animal logics" may be helpful in providing more intuitive data presentation and pilot response modality. BCI could be used to implement pilot commands or select the response mode desired through detection of intention. Effective and timely feedback of such BCI initiated actions to the human operator will be critical to acceptance.

Moving less critical tasking to BCI management might alleviate pilot workload and distraction if implemented with careful attention to human factors. An example might be offering refreshment or ergonomic adjustment on detecting related stress or discomfort levels.

Another less fraught application of BCI might be to assess general pilot alertness or mental state, and determine the subject of pilot attention. This information could be used to prompt appropriate pilot attention or otherwise modify the more conventional HCI appearance or operation.

We conceive of the following hierarchy of BCI applications to (onboard or remote) aircraft piloting, of decreasing risk level:

(*i*) Use of BCI to detect & classify pilot intention/attention and more rapidly initiate control commands would set a high bar for reliability and fidelity of BCI that we are unlikely to exceed anytime soon.

(*ii*) Use of BCI to detect & classify pilot intention/attention and set control response mode seems equally or more problematic except for low criticality functions,

(*iii*) Use of BCI to detect & classify pilot intention/attention and prime aircraft systems for faster response to the ensuing command via the conventional HCI may be more acceptable, but could result in disconcerting response variability.

(*iv*) Use of BCI to detect & classify pilot intention/attention to shape HCI mode or presentation.

(*v*) Use of BCI to detect & classify pilot intention/attention as a trigger for (more timely) prompts or warnings.

(*vi*) Use of BCI to detect & classify pilot intention/attention as input to (overriding) command and control decisions/actions. (One example of the last option might be the detection of pilot incapacitation (e.g., loss of consciousness) as a cue for engaging the autopilot &/or remote/backup pilot intervention.

5. Conclusion & Recommendations

Further improvement in our knowledge and understanding of animal logics and BCI are expected to lead to more effective HCI in the context of highly automated aerospace systems combined with crew multitasking. Doing so without degrading, let alone enhancing, expected levels of safety and system reliability will require implementations that fully mitigate the potential for unpredictable and nondeterministic system behavior and inappropriate operator response.

Early application of animal logics may occur in the design of HCI which are more intuitive and require less high level human operator attention for safe and effective man/machine interaction. As BCI capability and dependability improve, a range of practical application modalities is expected to emerge.

We propose herein a graduated approach to such applications that takes full cognizance of best practices in human factors engineering and systems engineering. Further research, for example simulator trials of potential applications, into the approaches suggested is recommended to guide the investigation, selection and use of animal logics and BCI in aerospace applications.

Such research should be informed by comprehensive systems engineering studies to identify promising operational applications and guide functional allocation between the vehicle crew (and remote operators), automated control, conventional HCI and BCI.

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BIOGRAPHY

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Richard Millar is an Associate Professor with the Naval Postgraduate School Department of Systems Engineering, based at the Patuxent River Naval Air Station. He has 35+ years experience in the design and development of gas turbine engines and their integration with aircraft propulsion & power systems. He has worked in this field at General Electric, United Technologies, Rolls-Royce, Boeing, Lockheed Martin and BAE Systems prior to joining NAVAIR in 2003.

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Robert Hiromoto is a Professor and former Department Chair in Computer Science Department at the University of Idaho (UI). His research focus is in the areas of computational algorithms and the design of wireless communication protocols. Dr. Hiromoto has had extensive experience in high-performance and parallel computing. His most recent work has been on parallel graphics rendering architectures, a set theoretic estimation approach to decryption, and the design of UAV communication protocols. Dr. Hiromoto was formerly a professor of computer science at the University of Texas at San Antonio (UTSA), and a staff member for more than 12 years in the Computer Research group at the Los Alamos National Laboratory.

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